'Public Transport Innovations in the Time of Covid-19': Crowdsourcing and Bus Telematics for Promoting Fuel Efficiency and Eco-Driving Practices on the EDSA Busway

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Abstract: Crowdsourcing through telematics and mobile platforms has been heavily researched for transport applications in the last decade, falling in the realm of intelligent transport systems (ITS). The value of crowdsourced data lies in enabling the participation of the 'crowd' for a human-centric, user-oriented, and reliable information system. On the other hand, there is a need for robust systems beyond traditional data collection methods, especially in public transport. Telematics is generally understood as a method of monitoring cars, trucks, equipment, and other assets by using GPS technology and onboard diagnostics to plot the asset's movements on a computerized map. This study demonstrates the power of crowdsourced open data for promoting fuel efficiency and eco-driving practices on bus operations through the pilot implementation of the EDSA Bus Efficiency Analysis and Monitoring System (BEAMS). The platform is integrated with *SafeTravelPH*, which public transport crowdsourcing app. Through collaboration with operators and drivers, the prototype collected real-time data on vehicle location, passenger boarding and alighting and vehicle occupancy feeds. An innovative approach in capturing vehicle operating parameters, including engine RPM, speed, and fuel levels, is implemented using image processing and artificial intelligence[1] (AI) techniques. Various fuel efficiency indices that can provide sound basis for the evaluation of bus driving behavior and fuel-efficient bus operations are presented.

Keywords: Public transport crowdsourcing, bus telematics, eco-driving, artificial intelligence

1. INTRODUCTION

1.1 Background

The manifestation of the COVID-19 pandemic in 2020 grossly affected the Philippine economy and prompted an emergency response from the national government to slow down the spread of the virus. On March 15, 2020, the President announced the Enhanced Community Quarantine (ECQ), a nationwide lockdown that stirred all sectors of the country, including public transportation. Travel restrictions were placed all over the country that severely disrupted all forms of transport except for essential travel. Only private vehicles were allowed at the time of the lockdown, while a few shuttle services were deployed under special

[1] The Oxford Dictionary defines artificial intelligence as "the theory and development of computer systems able to perform tasks normally requiring human intelligence, such as visual perception, speech recognition, decision-making, and translation between languages."

permits to facilitate healthcare workers reaching their work destinations.

It was then that the Department of Transportation (DOTr) found it opportune to move through with its Public Utility Vehicle Modernization Program (PUVMP) by implementing 31 rationalized bus routes in Metro Manila through a Memorandum Circular 2020-019 of the Land Transportation Franchising and Regulatory Board (LTFRB). Among these 31 routes was the EDSA Carousel - a dedicated bus route along the EDSA corridor running from Monumento to the Pasay Integrated Terminal Exchange (PITX) physically set at the median lane. The route is designed to ensure that EDSA buses operate at reliable travel time and consistent headways without the ramifications of mixed traffic congestion along EDSA. Bus stops were also placed along the median lane, either below pedestrian footbridges or aligned with the MRT-1 stations.

It is argued that the success of the EDSA Busway, being the backbone route of the metropolis, is crucial to improving the rest of Metro Manila's transportation system. Incremental improvements in the service can best be achieved with effective monitoring and data systems. It is in this context that key performance indicators should be regularly captured and monitored towards improving the operational efficiency and at the same time achieving financial sustainability of bus operations.

During the nationwide lockdowns, the University of the Philippines Pandemic Response Team, housed under the UP Resilience Institute (UPRI), was established as the University's initiative in providing knowledge and proposing solutions to the pandemic. The *SafeTravelPH* mobile application[2] and information exchange platform was borne out of the need to support contact tracing in public transportation alongside providing a long-term, more sustainable solution to transport planning and operations data needs. At the same time, an Energy Research Fund (ERF) project[3] was undertaken to promote fuel efficiency and eco-driving practices for bus operations along EDSA.

1.2 Research Objectives

This paper aims to establish the use case for crowdsourced data platforms for Philippine road public transport by evaluating the performance of the EDSA busway operations from the viewpoint of fuel efficiency and eco-driving principles. The overarching goal of the research is to propose a robust approach in bus telematics, given the national goal of modernizing public transport technology and operations in the Philippines.

2. EDSA BUSWAY

2.1 Study Area

About 30% of the total number of the public utility buses (PUB) in the Philippines operates in Metro Manila, the majority of which are city buses plying the stretch of Epifanio de los Santos Avenue or EDSA. As such, EDSA is considered the prime route among bus operators because of the exclusion of jeepneys for most of its stretch, wide carriageways appropriate to bus operations, and the most significant number of passenger flows generated by business districts (Makati and Ortigas) as well as several malls (Ayala Center, Megamall, SM City, Araneta Center). The use of public transport is continuously threatened by growing car ownership and

[2] Google Play Store. https://play.google.com/store/apps/details?id=ph.safetravel.app

[3] University of the Philippines Diliman Office of the Vice-President for Academic Affairs (OVPAA) Energy Research Fund (ERF) Project on "EDSA Bus Efficiency Analysis and Monitoring System (BEAMS): Promoting Bus Fuel Efficiency Through Promotion and Incentivization of Eco-driving Practices"

deteriorating public transportation service levels. The EDSA Carousel is designed as a 28-km route from Monumento (North of Metro Manila) to the SM Mall of Asia (South of Metro Manila) before terminating into the PITX. EDSA has six (6) lanes with a maximum width of over 20 meters per direction, and since implementation, the median lane has been dedicated to the EDSA Carousel.

The initiative has been met with several challenges. Firstly, travel demand remains uncertain, mainly brought about by varying quarantine restrictions. Secondly, the infrastructure was essentially an ad hoc augmentation measure to the EDSA-MRT3 services. As such, many bus stops were placed under the footprint of the existing MRT stations with constrained waiting areas and pedestrian footbridges that are not designed to carry queues of commuters. Lastly, travel demand on EDSA was based on the MMUTIS Update and Capacity Enhancement Project (MUCEP) conducted in 2015, which does not capture more recent travel demand patterns. Currently, the EDSA busway runs with about 300 operating units out of the 550 authorized units from 31 bus operators.

Figure 1. Image of the EDSA Busway

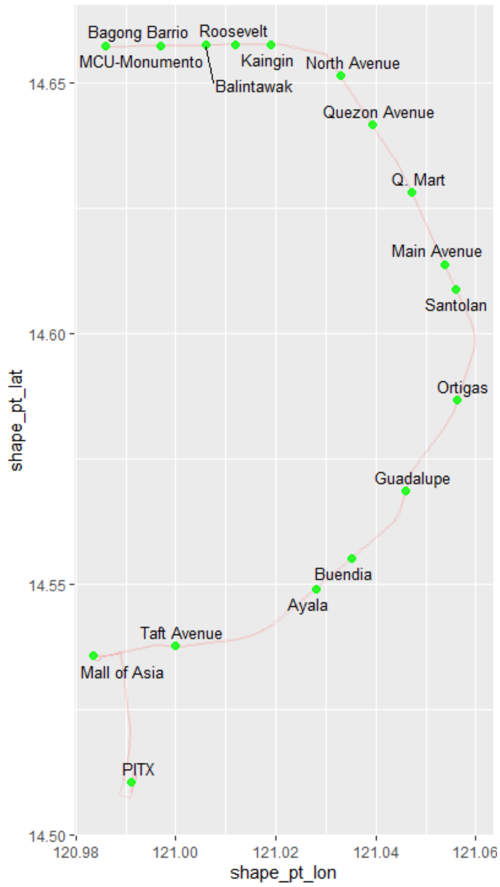


Figure 2. EDSA Busway Route and Stations

2.2 Initial busway operations

Surveys were conducted in Jan-Feb 2021 to determine headways and occupancies of buses that were part of the initial implementation of the EDSA Carousel. It is observed that bus arrivals and headways have been quite erratic at the time of the survey (Figure 3 and Figure 4). The average bus headway is 4.1 minutes for the northbound direction, while it is 2.2 minutes for the southbound direction. While this is so, it can reach up to 62 minutes before a bus arrives. On the other hand, it seems pretty clear from the survey that bus operators were complying with restrictions with average occupancies meeting the 50% passenger load limit (Figure 5 and Figure 6). It is noted that the implementation of the busway at this time was still very much in transition.

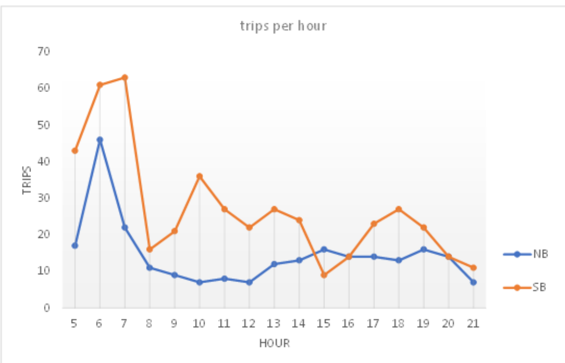


Figure 3. Bus arrivals per hour

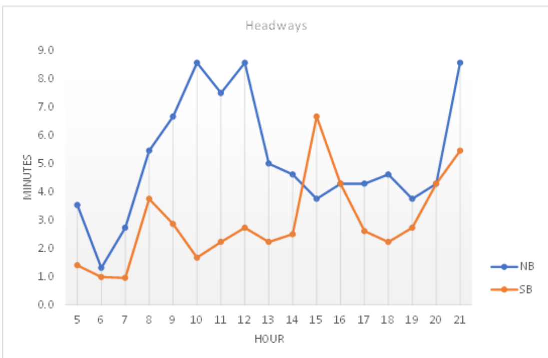


Figure 4. Bus headways per hour

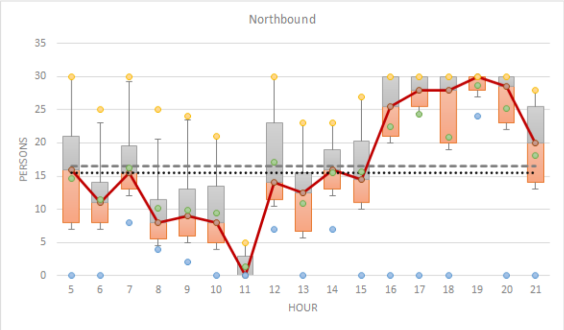


Figure 5. Boxplot of observed occupancies of southbound trips per hour

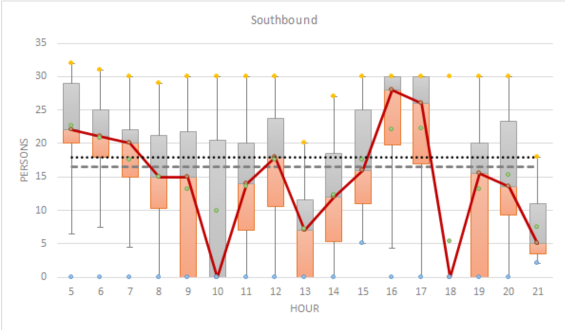


Figure 6. Boxplot of observed occupancies of southbound trips per hour

Source: ERF Bus Survey 2021

2.3 Need for bus efficiency monitoring

There is a need to continuously analyze and monitor the operation of buses along EDSA to improve the planning and control systems of concerned agencies and bus industry stakeholders, and general commuters. Bus telematics has often relied on Automatic vehicle location (AVL) and automatic passenger counter (APC) systems capable of gathering an enormous quantity and variety of operational, spatial, and temporal data. If such data are captured, archived, and analyzed correctly, it holds substantial promise for improving public transport performance by supporting improved management practices in areas such as service planning, scheduling, and service quality monitoring.

3. LITERATURE REVIEW

3.1 Potentials of eco-driving

Based on the recent data from the Department of Energy, the transport sector is 35% of total final energy consumption, growing at a rate of 4.1% per year. The sector emits 28% of greenhouse gases. Recent literature points out that operators can reduce up to 25% of their fuel consumption by training their drivers on eco-driving. This requires estimating parameters (such as speed, speed variation, acceleration/deceleration) where the vehicle would operate at optimal fuel efficiency, also called a “green area,” and continuously improve using real-time data.

According to Huertas, et al. (2018), the main obstacle of implementing the green area concept is the lack of an engine load gauge to guide drivers to operate the engine preferentially within this green area, and therefore the green area concept has been reduced to the RPM green band concept in traditional eco-driving techniques.

Existing literature points out that operators can reduce up to 25% of their fuel consumption by training their drivers on eco-driving. While there is no exact definition for eco-driving, there are established elements from best practices worldwide. Sivak and Schoettle (2012), in their presentation of information about effects on driver behavior on the fuel economy of light vehicles classified three (3) decision levels: Strategic decision (vehicle selection and maintenance); Tactical decision (route selection - road type, grade, congestion, and vehicle load) and Operational decisions (idling, speed, engine rpm, cruising, aggressive driving, air-conditioning)

Xu et al. (2017) found that the savings from eco-driving were comparable and better in some cases to the fuel consumption and emission improvements that can be achieved in switching to compressed natural gas (CNG) powered vehicles, a popular energy conservation strategy. While policies aimed at reducing CO_2 emissions thru eco-driving practice are effective, with impacts from 5% to 45% depending on the locations and kind of interventions, there are still conflicting views on the effectiveness of eco-driving in improving emissions and fuel consumption in congested city centers.

Sanguenitti et al. (2017) synthesized prior research on eco-driving behaviors that results in varying fuel consumption saving and outlined six (6) typology of driver's (and shop's/operator's) behaviors that can be the basis of interventions for holistic fuel savings in fleet management:

1. Driving (acceleration/deceleration, cruising, waiting, parking)
2. Cabin comfort (air-conditioning, ventilation, appliances)
3. Trip planning (travel routes, road types, time of the day of the travel)
4. Fueling (fuel type, time of day, and temperature when fueling)
5. Load management (occupancy, cargo, aerodynamics of vehicle selected)
6. Maintenance (changing oil, oil selection, tires selection, and inflation, engine maintenance schedule)

3.2 Fuel consumption savings and parameters

Limiting the discussion to engine operations, these eco-driving techniques can be re-stated as the techniques of reducing fuel consumption by restricting the engine to work within recommended operational ranges ("green area"), where the engine exhibits its highest energy efficiency (minimum fuel consumption). Usually, this range has been expressed as a constant range for RPM, and it is referred to as the engine RPM green band (DFT, 2009).

In a field trial with 1156 trips in two cities, deceleration rate, engine RPM, speed, and external factors such as congestion and road slope directly influence fuel consumption. (Lois et al., 2019). Similarly, driving styles can reveal the differences among drivers of the exact vehicle that can vary up to 5.5% fuel consumption reduction, with significant contribution from braking, acceleration, and standstill behavior (Ayyildiz et al., 2017). Meanwhile, around 50% of the fuel consumption of a city bus is consumed during acceleration (Ma et al., 2015).

Conversely, a decrease in fuel consumption in an urban area can be achieved when deceleration is minimized during smoother rides with less braking (negative deceleration). The fuel savings, however, depends on the type of the road and the reduction of maximum speed on each road type, but not on the number of stops per kilometer (Coloma et al., 2018). Recent work shows that engine energy efficiency also depends on engine load. Therefore, the engine RPM green band concept of eco-driving can be extended to an engine load—RPM green area, which corresponds to the load vs. RPM area where engines exhibit the highest energy efficiency.

Multiple regression analysis is a straightforward way of correlating vehicle information as independent variables to fuel consumption as a dependent variable (Lee and Son, 2011). Results from previous studies can be used to create a model based on relationships of variables that are significant in predicting fuel consumption. However, predicting accurately the fuel consumption level within the dynamics of driver's behavior, road conditions, and engine and vehicle performance can be too complex due to human bias and randomness (Delice et al., 2007), and the non-linearity of diesel engine dynamics and control system (Chiara et al., 2011).

In their study of the interaction of driving behavior and external factors, Lois et al. (2019) employed a sequential method in data analysis comprising factorial analysis, regression analysis, and path analysis for a dataset of 1,156 trips, 8,150 kilometers of travel, and 128 variables. Factorial and regression analyses were done to determine empirically important variables. Path analysis models the relationships among internal (engine RPM, negative acceleration, vehicle speed) and external (congestion, road slope) factors and fuel consumption. At $p<0.001$, the multiple regression method has an r-squared of 0.702, which indicates a strong correlation between independent variables and fuel consumption.

Meanwhile, the fuel consumption level and driving style evaluation model developed by Ma et al. (2015), departing from the regression and continuous variables modeling from other studies, used a decision tree-based classification algorithm called C4.5. The following reasons are the advantages of C4.5 over other data science methods:

- Its ability to get good classification predictions while requiring minimal computational resources is significant to the low-cost, low-capacity embedded system/telematics equipment of a vehicle. This can also encourage the widespread use of technology to enhance datasets and data randomness.
- Statistical significance and relative significance of factors can be outputted by decision trees methods and could inform drivers and fleet managers to optimize their operations.
- This decision tree method can process continuous input from the driver's telematics data.

This model used 7,500 acceleration samples based on recorded initial and shifting threshold velocities, gear shifting for acceleration, and acceleration/deceleration times. The accuracy of a two-level discrete classification driver evaluation model ("Good" or "Bad" driver) was 86.47%. In comparison, a five-level model reached 50% accuracy—generally, the more classification levels, the lower the accuracy rate.

3.3 Crowdsourcing

Monitoring and analysis of driver's performance via mobile phone GPS are pretty novel in the Philippine public transport regime, although several attempts have been made elsewhere. The study of Shinde and Ansari (2017) proposed an intelligent bus monitoring system for accident detection, emergency fails to switch, and drunk and drive authentication using GPS and RFID sensing. The study of Sultan et al. (2017) exploited crowdsourced user-generated data, namely GPS trajectories collected by cyclists and road network infrastructure generated by citizens, to extract and analyze spatial patterns and road-type use of cyclists in urban environments. Spatial data handling processes, including data filtering and segmentation, map-matching, and spatial arrangement of GPS trajectories with the road network, were used to address data deficiencies.

Mobile phone applications for transportation have been around for some time. Waze© has been a known brand as a decision support system for road navigation and trip making for private cars. Google provides web-based navigation with mode options. Waze itself utilizes machine learning and crowdsourcing in its backend navigation models. In the Philippines, several applications already exist that apply real-time monitoring but primarily for deliveries (Grab, Food Panda) or taxi services (Grab, Uber). Few in so far provide specifically for public transport. Sakay. ph since its creation has attempted to build itself as a multimodal platform for commuters.

Poblet et al. (2017) presents a comprehensive review of crowdsourcing platforms and methods and provide a very useful typology in understanding the role of the crowd based on the type of data be participation involved. This leads to four types of crowdsourcing roles based on i) type of data processed (raw, semi-structured, and structured data), ii) participants' level of involvement (passive or active) and, (iii) skills required to fulfill the assigned task (basic or specialized skills).

Recently, Falco and Kleinhans (2019) provided a review of over 100 digital participatory platforms (DPP) and presented a more comprehensive picture of the availability and functionalities of DPPs. They reported a renewed interest in citizen co-production of public services, especially given the financial pressures currently facing governments worldwide. Co-production generally refers to the public sector and citizens making better use of each other's assets and resources to achieve better outcomes and improved efficiency. In line with this stance, mobile applications and platforms created by professional developers through government challenges, prizes, apps competitions, and hackathons - where governments make their data available to produce new ideas and solutions - are widespread.

3.4 Collaborative governance

It is argued that there is a need to actively explore collaborative governance mechanisms as innovations to the decades-old public transport policy in the Philippines. Firstly, there is a need to identify policy gaps in the PUVMP implementation as there may be underlying structural constraints and bottlenecks in the policy environment. Secondly, there is a need to evaluate the institutional capacity of concerned national and local government agencies involved in the roll-out of the PUMVP. Lastly, there is a need to take stock of the responses of concerned public transport operations and the commuters at large concerning the policy performance of the PUVMP. Overall, there is a need to explore a multi-stakeholder approach in terms of sense-making and evaluate the present state of the public transport system in the country.

Governance scholars and practitioners have used collaborative governance (CG) as a strategy for decades to explore solutions to cross-boundary governance problems without a clear analytical framework to explain its mechanisms, especially collaborative dynamics. To address this, Emerson et al. (2012) proposed a pioneering integrated framework that defines collaborative governance broadly as "the processes and structures of public policy decision making and management that engage people across the boundaries of public agencies, levels of government, and the public, private, and civic spheres to carry out a public purpose that could not otherwise be accomplished." This provides a broad conceptual approach for situating and exploring components of CG systems, ranging from policy or program-based intergovernmental cooperation to place-based regional collaboration with nongovernmental stakeholders to public-private partnerships. This integrative framework consists of three nested dimensions, representing the general system context, the CG regime (GCR), and its collaborative dynamics and actions.

According to Howlett and Ramesh (2015), co-production, like other collaborative governance arrangements, discounts the fact that it is often practiced without knowing precisely under what conditions and constraints it is likely to succeed or fail. The authors say that each arrangement has its prerequisites for governing capabilities and competencies from both governments and non-state actors. To take a significant step forward in understanding co-production, it is necessary to clarify what resources are required at the individual, organizational and systemic levels.

It is noted that the exploration and application of collaborative governance approach in public transport require continuous engagement with various stakeholders to establish trust and synergies among the actors. As such, there are several research initiatives being undertaken by the UP National College of Public Administration and Governance (UP-NCPAG) including the development of design thinking-collaborative governance workshop, policy capacity survey, big data analytics, IoT, and the establishment of an information exchange platform.

4. METHODOLOGY

4.1 Public transport crowdsourcing platform

This study utilized crowdsourcing and collaborative governance approaches to gather real-time monitoring data on participating drivers and operators in the EDSA busway route through the deployment of the *SafeTravelPH* mobile app. The app enables real-time vehicle location and occupancy data monitoring and provides a highly-customizable platform for public transport data capture, analysis, visualization and reporting.

A pilot implementation of the proposed EDSA Bus Efficiency Analysis and Monitoring System (BEAMS) was conducted from October 20 to December 5, 2020 involving bus drivers of HM Transport, Inc. The prototype platform consists of ubiquitous devices, specifically a smartphone (Xiaomi POCO X3; 64 GB storage; 6 GB memory; running on Android 10); a USB to Type-C adapter; and a wide-angle USB web camera.

Figure 7. Prototype BEAMS platform

The prototype BEAMS platform provides measurements of bus vehicle locations at most every second when cellular signal availability is best. Bus occupancy data is generated from the bus driver’s interaction with the *SafeTravelPH* app’s passenger boarding and alighting buttons. Finally, the prototype captures the bus dashboard images using the wide-angle USB camera which is installed at an optimal position for maximum coverage of the various dashboard dial indicators. Bus vehicle operating parameters such as revolution per minute (RPM), speed and fuel levels are extracted from the dashboard images vis image processing and AI techniques.

Figure 8. Structure of SafeTravelPH app and platform architecture

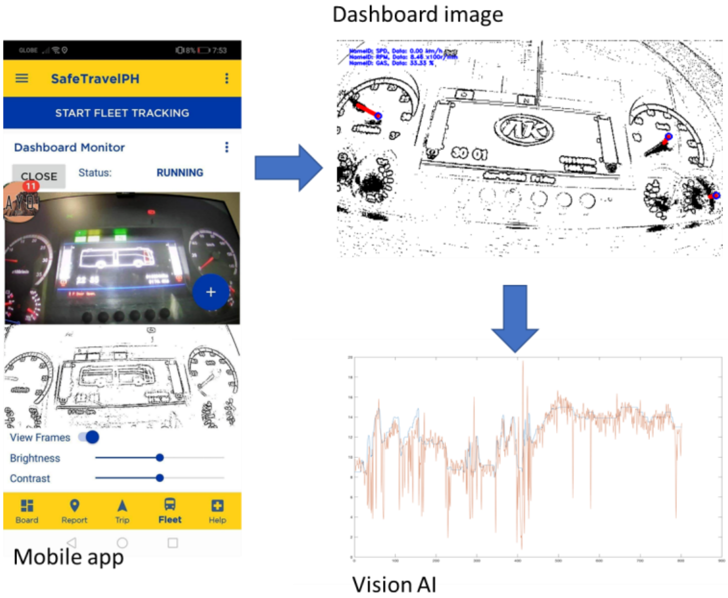


Figure 9. Image processing example

This paper uses a subset of the monitoring data from 23 November 2020 to 29 November 2020. Data before this period resulted from the testing and calibration of the platform to suit the operational characteristics of the participating operators and drivers. A week of data is used to provide a snapshot of week-long monitoring. Several factors contribute to the data quality that needs to be addressed. First, the accuracy of vehicle locations (Longitude and Latitude) depends on the smartphone GPS and different cover types like buildings and trees. Second, occupancy depends highly on drivers keying boarding and alighting accurately, thus requiring incentives, training, and quick feedback. Lastly, missing data tends to occur under poor connectivity, when the phone battery runs out, or when the driver turns off the phone during operating hours.

Bus fuel efficiency indices

The relationship between RPM and eco-driving has been described by Coloma, Garcia, and Wang (2018) that said average RPM is lower in eco mode than non-eco mode, and that negative acceleration is also lower in eco mode. The preceding paper also concluded that there is a strong correlation between fuel consumption and various parameters such as sloping, RPM, and speed. This research examined how dashboard image processing can effectively monitor RPM readings and how such a system can be utilized for eco-driving behavior analysis. However, the method posed challenges in also monitoring fuel consumption that could be useful in correlating consumption and speed at various points on the bus corridor.

The work by Ayyildiz, et al. (2017) presents a practical method in evaluating the effectiveness of eco-driving on freight transport based on a micro-scale approach. Their approach involves real-world driving patterns of the single vehicles and the drivers' individual behaviors are considered in evaluating instantaneous fuel consumption. One specific Key Performance Indicator (KPI) highly suggested in their study is the Energy Performance Indicator EPI, expressed in cl/(t ⁄ km) which indicates the average quantity of fuel required to transport 1 ton of freight.

$$EPI = \frac{AvgFuel}{\text{Mass} * 1000} \text{in} \left[\frac{\text{centiliter}}{\text{t} * \text{km}} \right]$$

In a similar fashion, efficiency indicators to evaluate public utility bus operations on the EDSA Busway can be explored and tested. As such, three operational parameters are proposed to provide the basis for an evaluation of the most fuel-efficient bus driving operations, namely:

- Total Distance Travelled, *TD*;
- Weighted Occupancy, *WOcc*, which is computed as the total of hourly values of the average number of passengers per hour multiplied by the distance traveled within the hour; and
- Weighted Speed, *WSpd*, which is computed as the total of hourly values of average speed per hour multiplied by the distance traveled within the hour

Based on the above parameters, the following fuel efficiency indices are proposed to be evaluated using fuel consumption in liters as the numerator and the various operational parameters as denominators. Take note that the units of the indicators are similar to EPI as opposed to mileage indicators which are measured in distance traveled per liter of fuel. The following fuel efficiency indices are proposed to compare the driving behavior and fuel consumption of bus drivers.

1) Distance Index, *DI*, measured in liters/km;
2) Occupancy Index, *OI*, measured in liters/passenger; and
3) Speed Index, *SI*, measured in liters/kph

5. DASHBOARD AI SYSTEM

5.1 Main Process

The Dashboard AI aims to provide real-time insight on the current performance of the vehicle (i.e., RPM, speed, and fuel levels) by directly observing the readings from the vehicle dashboard and providing analysis and insights afterward. With the help of computer vision, the analog displays of the speedometers are converted to digital information and are then processed to become a meaningful insight.

At the level of the driver, the application aims to provide an event detection system throughout the vehicle operation – whether an event of over-speeding occurs or perhaps a low fuel is detected. It can also offer general insight into the driver's behavior – how generally fast he drives or how much fuel is consumed in a period. On a collective scale, and with the help of GPS and other location services already available, the data gathered from different vehicles may provide insights on the average speed and RPM based on a certain street, path, or highway; as well as the invention may provide insight on the fuel consumption based on the vehicular model used (i.e., bus, car, van, etc.).

Figure 10 depicts the general workflow of the Dashboard AI. The operation starts by capturing an image of the vehicular dashboard and pre-processing it for transmission. Depending on the parameter, these pre-processed images are then grouped and are sent as a batch for lesser transmission overhead. On the server-side, the transmitted image frames are then read and post-processed to numerical data and interpreted depending on pre-defined parameters (e.g., maximum angular reading for speedometer, minimum angular reading for speedometer, etc.). The analyzed data are then sent back to the local side to display to users.

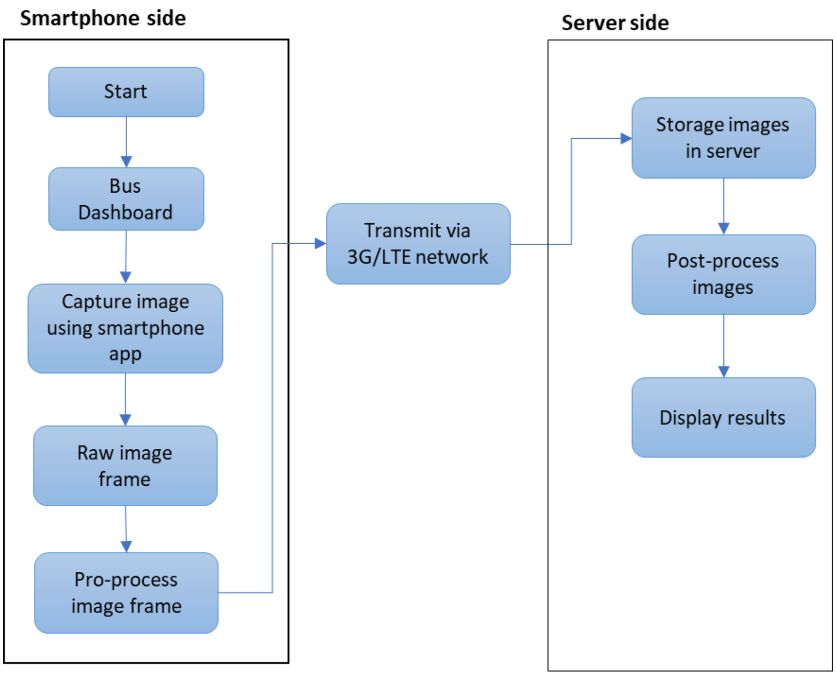


Figure 10. General Workflow of the Dashboard AI

5.2 Pre-processing

The structure of separating the processes into two parts (one in local and one in server) stems from two main underlying principles:

- To lessen the load of processing on smartphones, which consequently allows for wider device compatibility (both high-end and low-end smartphones will ideally be able to use the smartphone app)
- To aggregate the data collected from multiple vehicular monitoring systems which may be used for larger-scale analytics (i.e., general traffic speed at a particular road, the general speed of a particular vehicle type, etc.)

Figure 11 depicts the pre-processing for a raw image captured by the OTG camera. The main principle for pre-processing before transmission is to ease the processing load on the server-side without compromising the local side. The methods and processes contained are comparatively less intensive in terms of resources and runtime.

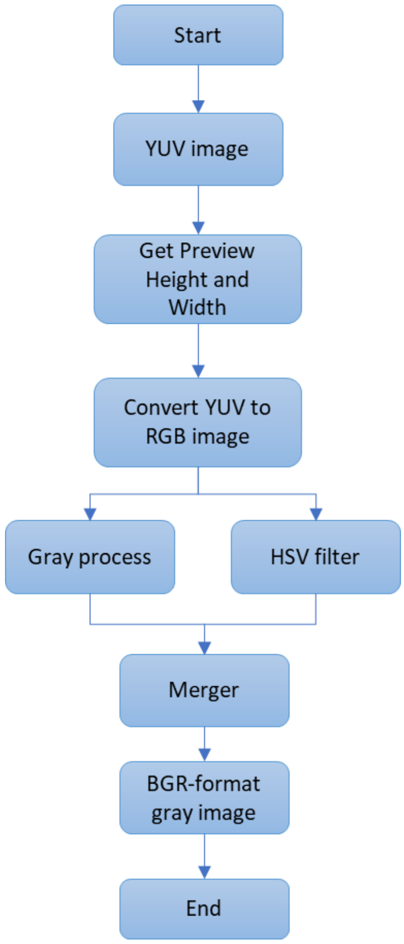


Figure 11. Pre-processing Workflow

Figures 12 and 13 show the raw image and processed image, respectively. It is noted that the calibration of the Dashboard AI depends much on the image capture conditions and the resulting raw image quality. This would include lighting conditions, image orientation, and occlusion levels. If these factors are controlled for, then it is expected that results will be more than satisfactory. On the other hand, the pilot implementation necessitated incorporating smoothing algorithms to address spurious readings. This was achieved through post-processing steps.

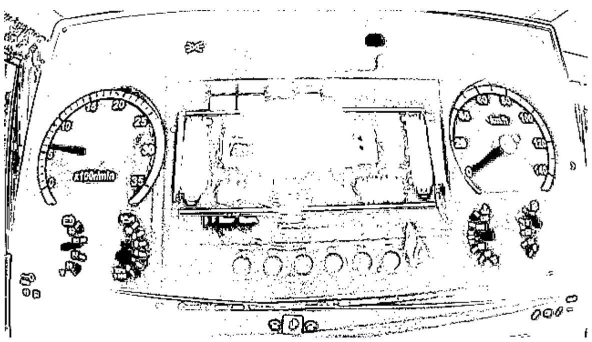


Figure 12. Raw image

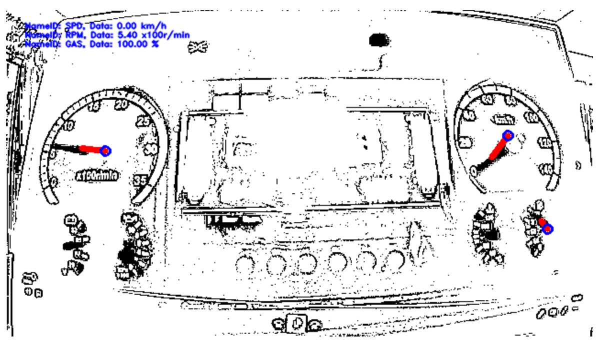


Figure 13. Processed image

Figure 14 presents the automated file management and process workflow to generate AI readings from a batch of raw images. The automatic process is necessary since many raw images are processed due to the high frame rate. The prototype system has been tested at ten frames per second, although the final data sets were sampled at two frames per second to reduce data size.

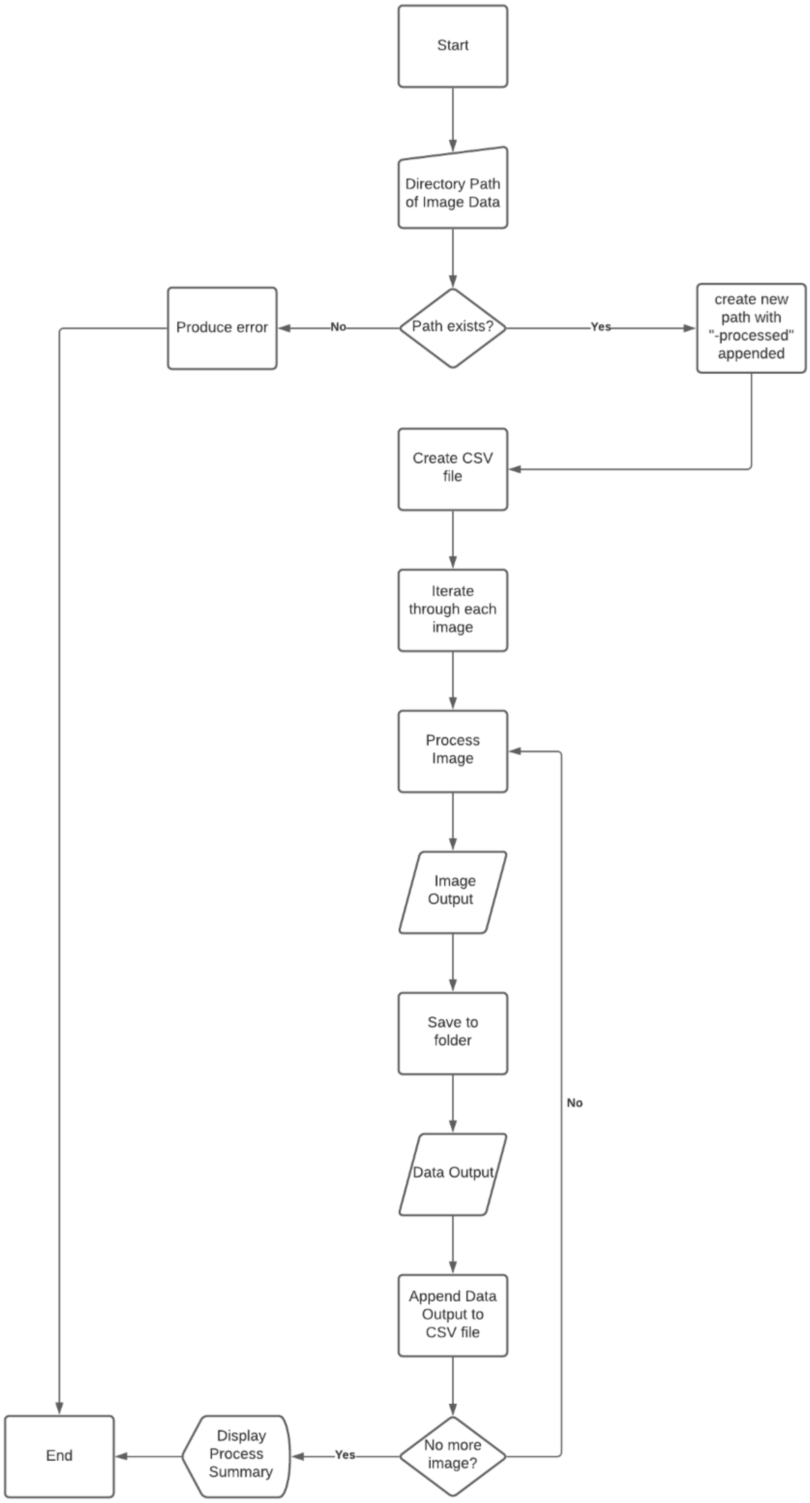


Figure 14. File Processing Workflow

5.3 Post-processing

Figure 15 depicts the post-processing of batched image data transmitted via the 3G network. The server's process workflow produces primarily two (2) outputs: a CSV file containing the value readings per frame and a directory of processed images for validation. A smoothing algorithm is added to smoothen the data acquired for the post-process of the AI readings. Two modes are available: (a) Thresholding and (b) EWMA.

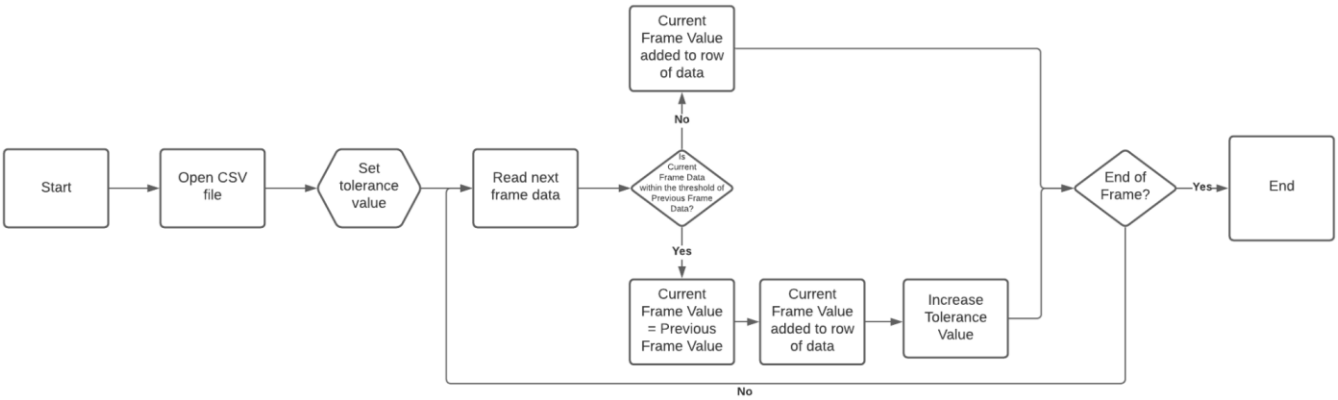


Figure 15. Post-processing Workflow

Mode 0: Thresholding

The thresholding method lies on the principal assumption that the dial reading cannot jump at a very high reading within a split second. With such a basis, it means that the next frame reading should be within a threshold from the previous frame; and a big jump on reading indicates an error in reading. If such a scenario happens, the current reading is discarded, and the previous frame is instead accepted as the correct, current reading. The tolerance threshold is then increased. The complete workflow is shown in the figure below: Currently, the base tolerance for RPM, SPD, and GAS are 1.25, 8, and 16, respectively, while the steps for each encountered error reading are 0.5, 1.2, and 4. These figures are precise to the current bus model used for prototyping.

Mode 1: EWMA

The second available mode for smoothening a dataset is the Exponential Weighted Moving Average. Using the CSV-formatted dataset, Mode 1 will convert the dataset to a panda DataFrame, and feed it to a library function `ewma().mean()` with the following parameters: *alpha = 0.7* and *ignore_na = True*.

5.4 Accuracy assessment

The following improvement has been observed from a sample dataset of a Manguiran bus trip. Initially, without the smoothening post-process, the reading accuracy is at 48.9%. Figure 16 shows the comparison between the manual task and the AI reading.

For Mode 0, which uses the Thresholding approach, a significant increase in the accuracy of the readings has been observed. Except for the time duration wherein occlusion has heavily occurred, the data generally seemed closer to the accurate readings. This method's accuracy is 71.2%, as shown in Figure 17. As for Mode 1, which uses EWMA for smoothening, there was a further decline in accuracy of the AI reading, with a rate of 44.8%. Although, to note, as compared to Mode 0, the recovery of EWMA from an occlusion (particularly in the 5:43:00 mark) is more rapid. This is shown in Figure 18.

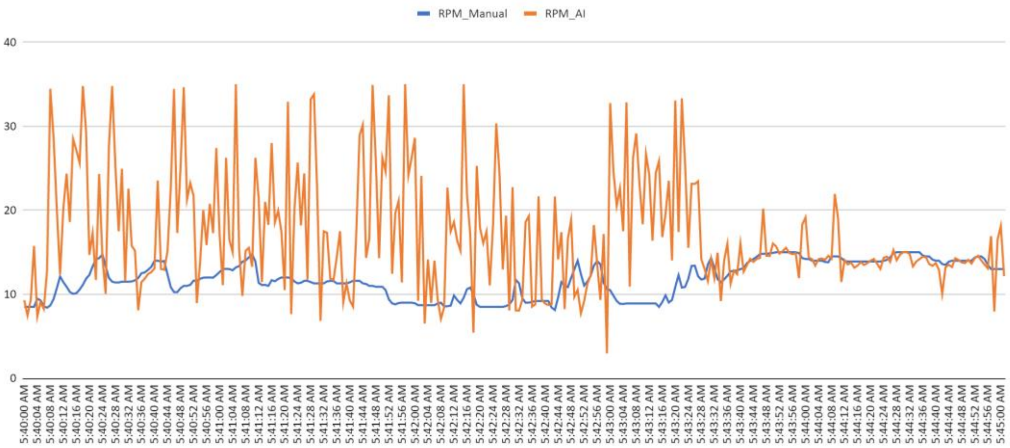


Figure 16. Comparison of Manual and Original AI Results

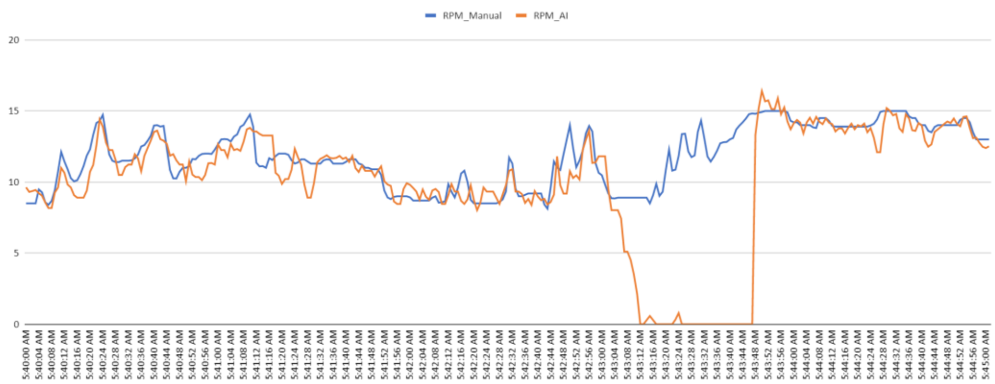


Figure 17. Comparison of Manual and Smoothened AI Results- Mode 0

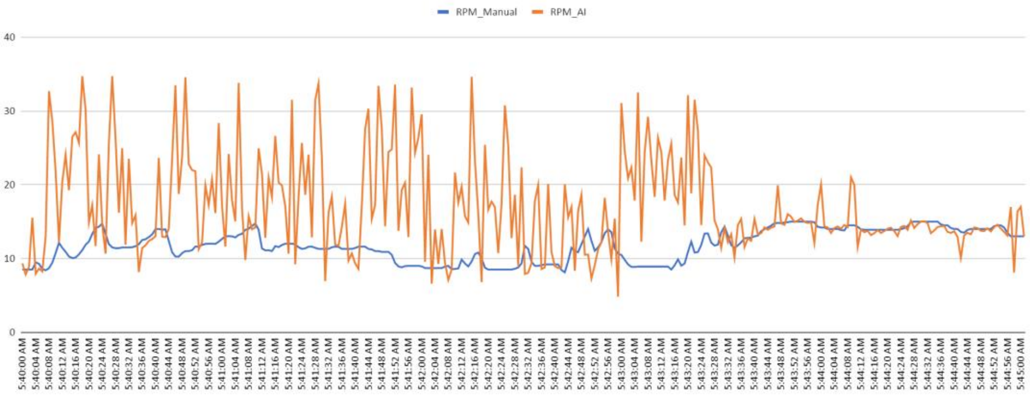


Figure 18. Comparison of Manual and Smoothened AI Results- Mode 1

5.5 Real-time RPM monitoring and eco-driving evaluation

Although speed detection has been already commercially available such as the Waze app, the Dashboard AI tries to integrate the vehicular behavior detection as close as possible to the driver, literally. With a camera in front of the dashboard, monitoring is straightforward. It does not require the transmission of location (which generally is power-consuming) to deduce the speed and other parameters via server. Essentially, with dashboard AI, monitoring is localized.

With the application in place, the detection system for vehicular driving is improved by lessening the burden for the drivers to look up the street and down the dashboard routinely. Ideally, with the Dashboard AI, the driver will be able to focus on the street and will just be notified when certain events (over-speeding, low fuel) happen through an alarm or voice alert. It is noted that many public transport vehicles in the Philippines still exist under the analog system. Therefore, the developed application is expected to provide utility not only to drivers and operators but also regulators and policymakers.

5.6 Robustness of AI

Dietterich (2017) highlighted the need for Robust AI and mentioned at least five aspects of robustness that require attention from the viewpoint of high-stakes applications. First, systems need to be robust to errors committed by their human operators. Second, high-stakes systems must be robust to mis-specified goals. Third, high-stakes systems need to be robust to cyberattack. Fourth, AI systems need to be robust to errors in their models of the world—that is, to places where their models are explicitly incorrect. Finally, AI systems need to be robust to unmodeled aspects of the world. The work also suggests key approaches for improving the robustness of AI systems and categorizes them into two, namely, dealing with ‘Known Unknowns’ and that of ‘Unknown Unknowns’.

At this point, it is safe to say that the present use case does not require a high level of robustness. Nonetheless, attention was given to ensure reliability and interpretability of the results. The need to increase robustness will be a subject of future research.

6. INITIAL RESULTS AND DISCUSSION

Figure 19 presents the fuel monitor by driver on December 3, 2020, during the pilot implementation of the EDSA-BEAMS prototype. The fuel consumption and total kilometer reading were requested from actual company records. It is noted that there is a linear relationship between kilometers traveled and fuel consumption. It should be emphasized that one cannot instantly determine who among the drivers is the most fuel-efficient just by looking at the fuel monitor.

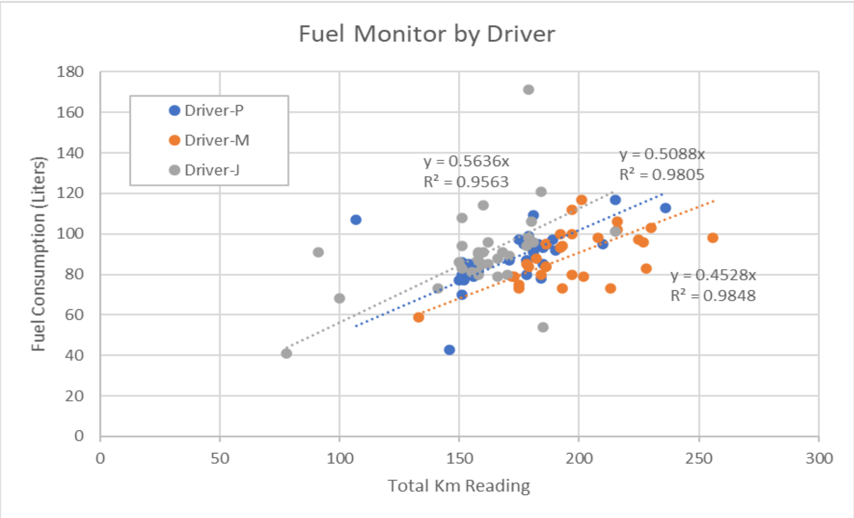
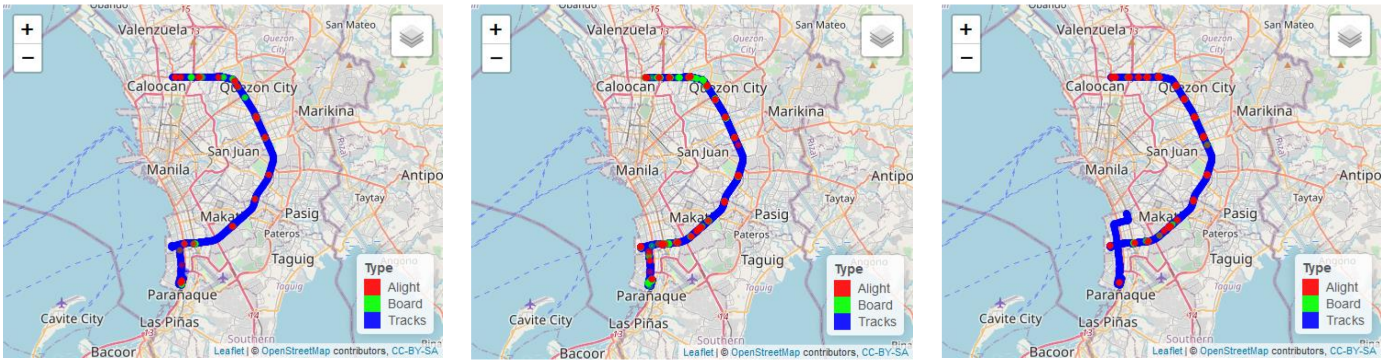


Figure 19. Fuel Monitor by Driver

Table 1 shows the performance statistics for the three drivers who participated in the pilot implementation of the BEAMS platform. Figures 20 and 21 present the GPS vehicle feeds and occupancy heatmaps per participating driver based on the SafeTravelPH public transport crowdsourcing app. Figure 22 presents the passenger load profile of the driver. And passenger load profile captured using the SafeTravelPH app and platform. It is noted that the data analytics platform is still under development and, therefore, might require re-validation.

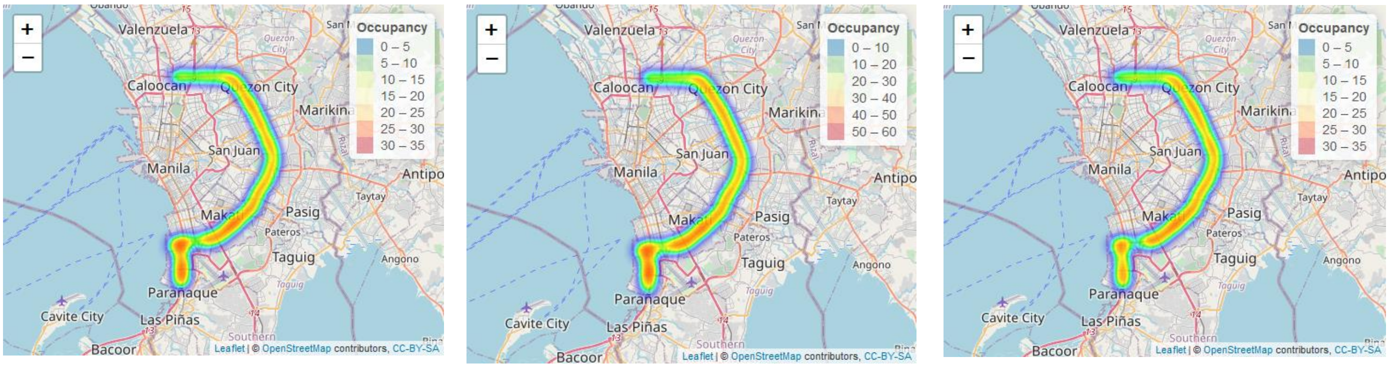
Table 1. Driver Performance Statistics on December 3, 2020

	Driver P	Driver M	Driver J
Time start	10:00:00	10:00:01	10:00:01
Time end	9:59:59	9:59:59	9:59:59
Time duration	12.5 hours	13.31 hours	13.93 hours
Total distance traveled	152.61 km	167.79 km	161.13 km
Average speed	15.58 kph	16.96 kph	14.04 kph
Total boarding	68	451	204



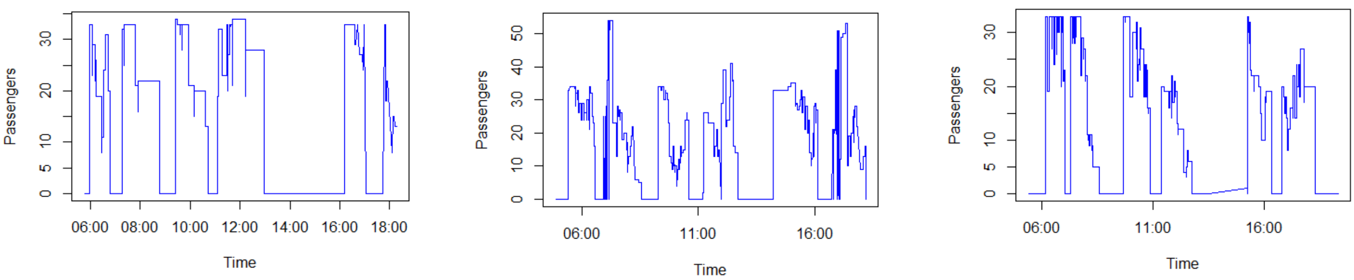
Driver P DriverM Driver J

Figure 20. SafeTravelPH GPS Vehicle Feeds by Driver



Driver P DriverM Driver J

Figure 21. SafeTravelPH Occupancy Heatmap by Driver



Driver P Driver M Driver J

Figure 22. SafeTravelPH Passenger Load Profile by Driver

Table 2 presents the evaluation of the various performance parameters for each participating driver. Table 3 and Figure 23 show the computation of each driver's different fuel efficiency indices. Based on the results, Driver M consistently exhibits the lowest values under each fuel efficiency index compared to Driver P and Driver J, indicating that Driver M has the lowest fuel consumption among other drivers and is deemed the most fuel-efficient.

Table 2. Performance Parameters

	Total Distance Travelled (km)	Weighted Occupancy (passengers)	Weighted Speed (kph)	Fuel Consumption (liters)
Drive P	152.6	17.8	16.1	95
Driver M	167.8	23.2	18.5	80
Driver J	161.1	16.6	17.3	96

Table 3. Fuel Efficiency Indices

	Distance Index (liter/km)	Occupancy Index (liter/pax)	Speed Index (liter/kph)
Driver P	5.3	5.9	0.62
Driver M	3.5	4.3	0.48
Driver J	5.8	5.5	0.60

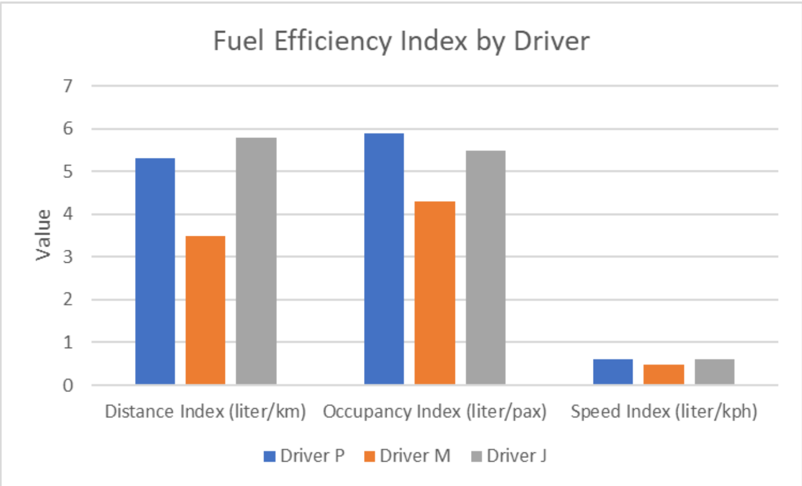


Figure 23. Fuel Efficiency Index by Driver

7. CONCLUSIONS

This study successfully demonstrated bus telematics and big data analytics through crowdsourcing and open platforms in analyzing road public transport performance. In the case of EDSA Busway, this paper analyzed the performance of buses using the sample monitoring and crowdsourced data from December 3, 2020, from the viewpoint of fuel efficiency and eco-driving.

The success of this experiment falls on both technical soundness and effective partnerships, i.e., operators, drivers, commuters, and developers working together in providing, storing, and analyzing data from an open platform that crowdsource from mobile phone data feeds. It is also crucial that the developers and analysts offer feedback on the analysis to incentivize the drivers to continue keying in the necessary inputs. Regular feedback to the data providers (drivers and operators) also motivates cooperation which is key to the crowdsourcing aspect of the platform.

More research and development efforts are needed for the AI methods deployed in this study towards a holistic decision support system to improve bus planning and eco-driving policy. For instance, as demonstrated by the RPM readings, the dashboard readings should be efficiently matched with locational readings to relate consumption and driving behavior to the design of the bus corridor and bus operational decisions. Nonetheless, this research has shown promise in crowdsourced real-time data processing for EDSA Carousel that can be further developed -an innovation hatched during the pandemic.

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